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Exploring Governance Failures in Australia: ESG Pillar-Level Analysis of Default Risk Mediated by Trade Credit Financing

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Abstract

This study examines the impact of overall Environmental, Social, and Governance (ESG) performance and its pillars on the default probability of Australian-listed firms. Using a panel dataset spanning 2014 to 2022 and applying the Generalized Method of Moments (GMM) regression, we find that firms with higher ESG scores exhibit a significantly lower likelihood of default. Disaggregating the ESG components reveals that the Environmental and Social pillars have a negative association with default risk, suggesting a risk-mitigating effect. In contrast, the Governance pillar demonstrates a positive relationship with default probability, which may reflect potential greenwashing behavior or an excessive focus on formal governance mechanisms at the expense of operational and financial performance. Furthermore, the analysis identifies trade credit financing (TCF) as a partial mediator in the ESG–default risk nexus, indicating that firms with stronger ESG profiles rely less on external short-term financing, thereby reducing their default risk. These findings provide valuable insights for corporate management, investors, regulators, and policymakers seeking to enhance financial resilience through sustainable practices.

Keywords: ESG; ESG pillars; probability of default; trade credit financing

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1. Introduction

The intersection between Environmental, Social, and Governance (ESG) performance and firm outcomes has garnered increasing attention from both academics and industry professionals in recent years. ESG is no longer a peripheral consideration; it has become a central pillar in shaping corporate behavior and investment decisions (He et al., 2023). As stakeholders grow more attuned to sustainability, firms are increasingly integrating ESG principles into their strategic frameworks (Kotsantonis et al., 2016; Sciarelli et al., 2021; Dmuchowski et al., 2023). ESG scores, which aim to capture a firm's ethical conduct, sustainability performance, and governance strength, are now key signals used by investors to assess not only a firm's reputation but also its long-term financial viability (Tarmuji et al., 2016; Landi & Sciarelli, 2019).

Despite the growing body of research linking ESG to financial performance (Aboud & Diab, 2019; Minutolo et al., 2019; Chen & Xie, 2022), a crucial gap remains: the role of ESG in shaping firm default risk, i.e., the probability that a firm will be unable to meet its debt obligations, has not been sufficiently explored. Yet, understanding how ESG impacts default risk is essential. For investors and creditors alike, default risk is a direct measure of financial stability and resilience, affecting not only asset pricing but also lending terms and risk premiums. Recent evidence suggests that ESG plays a crucial role in managing firm-level credit risk (H. Li et al., 2022); however, the mechanisms and differential effects across ESG components remain unclear.

Most extant literature treats ESG as an aggregate score, thereby obscuring the nuanced and potentially divergent roles played by its components, environmental (E), social (S), and governance (G). However, each pillar captures distinct dimensions of corporate behavior, and their relevance can vary dramatically across sectors (Bouslah et al., 2013; Girerd-Potin et al., 2014). For instance, the E pillar reflects a firm's carbon footprint and environmental compliance (Limkriangkrai et al., 2017; Bissoondoyal-Bheenick et al., 2023), while the S pillar relates to labor standards, community relations, and supply chain practices. The G pillar, by contrast, encompasses board effectiveness, ethical standards, and executive accountability (Broadstock et al., 2021). It stands to reason that each of these may exert distinct pressures, either mitigating or aggravating a firm's default risk profile.

Importantly, while ESG has often been framed as a mechanism for reducing risk, this assumption may not hold uniformly, especially in markets like Australia. The Australian context is uniquely informative: its economy is heavily weighted toward resource-intensive sectors such as mining and energy, where environmental and social controversies are more frequent and governance complexities more pronounced. These sectors face increasing scrutiny from investors, regulators, and civil society, intensifying the stakes of ESG misalignment. Moreover, Australia's robust regulatory environment and growing base of institutional investors amplify the influence of ESG practices on market perceptions and financing outcomes. Thus, ESG could play a double-edged role, i.e., reducing default risk for some firms while introducing new risks or exposures for others, depending on how ESG practices are implemented and perceived.

Against this backdrop, our study examines the relationship between ESG and firm default risk from a novel perspective. We draw on a sample of 161 publicly listed Australian firms over the period 2014–2022, a time of rising sustainability awareness and regulatory tightening. Uniquely, we disaggregate ESG into its three pillars to better understand their contributions to firm stability. Furthermore, we explore how ESG affects firm risk across different time horizons by analyzing short-term (1-month), medium-term (6-month), and long-term (12-month) probabilities of default (PD). The PD measure is obtained from the Credit Research Initiative (CRI) of the National University of Singapore (NUS). Based on the forward-intensity framework developed by Duan et al. (2012), the CRI default probabilities provide forward-looking estimates of a firm's likelihood of default over specified horizons of 1, 6, or 12 months. They are generated by a proprietary quantitative model that links historical default events to firm-specific accounting variables, market-based indicators such as equity volatility, and macroeconomic conditions (Credit Research Initiative of the National University of Singapore, 2022). The model is calibrated on a global dataset covering both developed and emerging markets, and then applied to individual firms, including Australian companies, to produce comparable PD estimates across countries. ESG indicators are not part of CRI's modelling framework. This means the PDs used in our analysis are generated independently from ESG inputs, allowing us to assess the ex-post relationship between ESG performance and credit risk. However, ESG characteristics may still be indirectly related to PD through their correlation with financial and market variables embedded in the CRI model, such as leverage, profitability, and volatility. By controlling for these factors, our study isolates the potential contribution of ESG performance to variations in default risk.

In addition to direct effects, we also investigate trade credit financing (TCF) as a potential mediating factor in the relationship between ESG and default risk. Trade credit, an essential source of funding for informal, may be influenced by a firm's ESG reputation, especially in supply chain–intensive industries. Exploring this mediation provides fresh insights into how ESG performance translates into real financial flexibility and resilience.

Methodologically, we apply the Generalized Method of Moments (GMM) estimation technique to control for endogeneity concerns common in panel data, ensuring robust inference. Our results indicate that while overall ESG performance reduces default risk, the story becomes more nuanced when pillars are examined separately. E and S pillar scores are negatively associated with default risk, consistent with the risk-reduction narrative. However, the governance pillar reveals a positive association, suggesting a potential overemphasis on formal governance mechanisms at the expense of operational risk management. Our findings remain robust across various specifications and offer several key contributions. First, we enrich the literature by providing empirical evidence on how ESG affects default probabilities, a more direct and actionable risk metric than general financial performance. Second, we demonstrate that not all ESG components are equally risk-relevant, a finding with significant implications for both rating agencies and portfolio managers. Finally, by introducing trade credit financing as a mediator, we offer a novel explanation for the mechanism through which ESG performance translates into firm solvency.

The rest of this paper proceeds as follows: Section 2 reviews the relevant literature; Section 3 outlines the theoretical framework and develops hypotheses; Section 4 details the dataset and methodology; Section 5 presents and interprets the empirical results; and Section 6 concludes with a discussion of theoretical and practical implications, as well as suggestions for future research.

2. Literature Review

2.1. ESG and Firm's Probability of Default

In terms of the connection between ESG and a firm's default risk, previous studies have explored this influence through various ESG frameworks. Specifically, Palmieri et al. (2023) examine the impact of ESG performance, combined with industry and stock index, on firms' probability of default in a sample of 211 European listed firms from 2013 to 2022. Their findings suggest that improvements in environmental scores can decrease the likelihood of default. They also conduct examinations in EU banks during the same period on the role of business models and ESG pillars in relation to banking default risk and find that environmental pillars contribute to mitigating default risk in both wholesale and retail banks. However, the governance pillar can reduce the risk in investment banks. Meles et al. (2023) indicate the negative impact of green innovation measured by environmental innovation score on the firm's default risk across 35 different European nations from 2003 to 2019. H. Li and Hu (2025), H. Li et al. (2022), and Shang et al. (2025) explore the influence of ESG practices/ratings on Chinese default risk and show that better ESG practices/ratings mitigate the default risk of companies. Unlike other studies, Do and Vo (2023) analyze the effect of mandatory ESG disclosure on companies' default risk by utilizing a sample of 17 emerging nations from 2008 to 2018. They use mandatory ESG regulation instead of ESG scores or ESG ratings, indicating that it can support default risk mitigation. Liu and Zhang (2024) examine how default risk is influenced by ESG performance in Chinese family companies from 2015 to 2022, noting that family businesses with higher ESG performance are less likely to face bankruptcy situations. When examining the impact of individual factors in more detail, they find that both environmental and social pillars have a negative association with firm default risk. Maquieira et al. (2024) also investigate the ESG-default risk relationship in family firms, but they expand to a worldwide context. Their findings, similar to Liu and Zhang's (2024) study, conclude that ESG, E and S pillars negatively affect the default risk of companies. Atif and Ali (2021) examine whether ESG disclosure is associated with default risk and find the positive impact of ESG on Merton's default distance. They also indicate the negative relationship between ESG disclosure and credit swap spread. These results mean that higher ESG disclosure leads to lower default risk. Kanno (2023) finds that firms can rely on ESG performance to predict their default risk. Aslan et al. (2021) point out that firms with better ESG performance have lower credit default.

2.2. Mechanisms Linking ESG and a Firm's Probability of Default

Trade credit is a short-term, delayed payment that suppliers use to motivate customers to increase the number of ordered products. Businesses buy and sell products concurrently, usually on credit. A supply chain may have numerous linkages between suppliers and customers. Due to most firms borrowing from their sellers and giving credit to their buyers simultaneously, they are vulnerable to default risk. As a result, a business facing its customer's payment default may experience liquidity problems and face a default possibility related to payment risk to its seller (Boissay & Gropp, 2013). Furthermore, sellers may control buyers since their suppliers can threaten customers if they do not pay on time, especially when they are dependent on these suppliers. Jacobson and Von Schedvin (2015) demonstrate that suppliers who grant greater trade credit are more vulnerable to their customers' failures, therefore facing a noticeable probability of bankruptcy. If the seller offers trade credit for a portion of the purchase, the buyer must borrow the money from the bank because they do not have the cash to cover the unit's manufacturing cost initially. It can use its cash flow from other operations as collateral to secure this loan, which will be used to repay the bank if the buyer defaults and fails to pay the seller (Biais & Gollier, 1997).

ESG facilitates access to cheaper alternative sources of capital: companies with strong ESG performance can borrow from banks or issue bonds at lower costs, thereby reducing their reliance on trade credit. Banks view CSR issues as risks and respond by offering less alluring loan arrangements. The existence of guarantees with creditors is crucial for mitigating concerns (Goss & Roberts, 2011). Their research provides clear evidence that companies with high CSR ratings tend to pay significantly lower interest rates on bank loans compared to those with poor CSR performance.

Sustainability reporting (a component of ESG) is positively associated with both financial performance and operational efficiency. Higher operational efficiency often includes better working capital management (Buallay, 2019). Research demonstrates that effective management of accounts receivable and accounts payable is key to improving financial performance (Baños-Caballero et al., 2012). Large companies with strong ESG performance are often able to negotiate more favorable terms instead of extending payment periods, as they are perceived as reliable and high-quality clients (Klapper et al., 2012).

3. Theoretical Framework and Hypothesis Development

Several theoretical perspectives suggest that ESG performance may influence firm default risk. Based on stakeholder theory (Freeman, 1994), a crucial perspective holds that businesses that take into account the interests of all parties involved, not just shareholders, develop closer bonds with their staff, clients, suppliers, and local communities. Strong stakeholder connections can lead to lower operational risks, enhanced crisis resilience, and more stable revenues, all of which reduce the likelihood of default. Secondly, legitimacy theory (Suchman, 1995) suggests that when businesses conform to social norms and expectations, such as ESG standards, they aim to gain legitimacy. Strong ESG performance enhances a company's chances of maintaining regulatory support and public trust, both of which can be crucial in times of economic crisis. Additionally, signaling theory (Spence, 1973) suggests that lenders and investors may interpret strong ESG performance as a reliable indicator of a company's quality, which could result in improved lending terms and a reduced likelihood of default. A business that makes significant investments in ESG activities conveys that it is forward-thinking, well-managed, and compliant with laws and social norms. By encouraging the disclosure of non-financial information, ESG may help reduce risk (Kanno, 2023). Furthermore, the Risk Management Perspective (Godfrey, 2005) states that proactively managing ESG risks minimises the likelihood of penalties, legal action, supply chain disruptions, and reputational harm, all of which can lead to financial difficulties. Collectively, these theoretical lenses converge on the expectation that robust ESG performance contributes to enhanced financial stability and reduced default risk. Therefore, we propose the following hypothesis:

Hypothesis 1 (H1). *Firms with higher overall ESG scores have a lower probability of default risk than firms with lower ESG scores.*

We propose that different ESG pillars may have other implications on business risk (Bouslah et al., 2013). The three ESG factors engage a wide range of stakeholders and have the potential to impact financial and risk indicators (Godfrey et al., 2009; Girerd-Potin et al., 2014). Investors' differing opinions about the importance of each ESG feature could lead to different market responses. Moreover, the degree to which the data are measurable and trustworthy may also influence how significant people perceive the three dimensions to be (Derwall & Verwijmeren, 2007). Because of this, we do not assume a strictly negative impact; instead, we propose that individual ESG pillars have a considerable impact on business default risk in their own right. Therefore, we develop the following second hypothesis.

Hypothesis 2 (H2). *A Firm's probability of default is significantly impacted by each of the three individual ESG pillar scores separately.*

Stakeholder theory suggests that businesses should consider the interests of all parties affected by their activities, not just shareholders, but also customers, suppliers, employees, and the broader community. This framework is widely applied in the literature to understand the role of trade credit financing in shaping firm performance. Specifically, it has been argued that when a firm reduces its reliance on bank loans and simultaneously increases its dependence on trade credit, it may signal financial constraints or reduced access to traditional financing channels, potentially undermining its overall financial health.

Investments in ESG performance are closely tied to a firm's cash flow, which directly influences its ability to meet short-term financial obligations and manage default risk (H. Li et al., 2022). Adequate cash flow serves as a buffer against financial distress, and ESG-related initiatives, by improving operational efficiency, stakeholder trust, and reputational standing, may enhance a firm's liquidity position. According to foundational models of default risk by Black and Scholes (1973) and Merton (1974), the probability of default is influenced by the ratio of a firm's asset value to its liabilities. From this theoretical foundation, we assess default risk from both supplier and customer perspectives, recognizing that firms often operate as both providers and recipients of trade credit. Delays in payments, whether in accounts payable or receivable, can disrupt balance sheet equilibrium, particularly in terms of working capital requirements. Trade credit imbalances thus elevate the risk of insolvency by constraining liquidity. In this context, strong ESG performance fosters transparency and reputational capital, enhancing access to trade credit and other valuable financial resources. Notably, firms with robust ESG or corporate social responsibility (CSR) records tend to enjoy lower equity financing costs (El Ghoul et al., 2011), suggesting that ESG excellence can indirectly alleviate liquidity risk and, by extension, default risk. This observation forms the basis for the third hypothesis.

Hypothesis 3 (H3). *Trade credit financing significantly mediates the relationship between a firm's probability of default and ESG or individual pillar scores.*

4. Research Design

4.1. Data and Sample

Our study selects all non-financial listed firms in the Australian stock market from 2014 to 2022 as the study sample. Based on data availability, the final panel dataset comprises 161 firms, resulting in 1412 firm-year observations. ESG overall scores and individual pillar scores were extracted from LSEG. Firm's default probability data are obtained from the CRI database of the National University of Singapore (NUS). Control variables were obtained from Compustat and firms' publicly available annual reports.

4.2. Variable Measurement

4.2.1. Independent Variable: ESG and Its Pillars

We obtained the ESG overall score and single pillar scores from LSEG. LSEG ESG data are compiled from publicly available sources, including company annual reports, CSR/sustainability reports, stock exchange filings, and reputable news sources, and are standardized to ensure cross-country comparability. The scoring methodology evaluates a firm's performance across three main dimensions: Environmental (E) covering areas such as resource use, emissions, and environmental innovation; Social (S) including workforce policies, human rights, community engagement, and product responsibility; and Governance (G) encompassing management structure, shareholder rights, audit quality, and CSR strategy. Each pillar score is calculated based on weighted category scores, which are normalized to a scale from 0 (lowest performance) to 100 (highest performance). The overall ESG score is a weighted aggregation of the three pillars, reflecting a firm's relative sustainability performance within its industry peer group.

Table 1 illustrates annual mean scores and standard deviations from 2014 to 2022 for overall ESG and individual pillars, E, S, and G, based on 1412 firm-year observations. The variations across the ESG overall score and its individual pillar scores are highlighted in Table 1, which uses a color-coding scheme with green indicating the highest values and red indicating the lowest. Additionally, the maximum and minimum values are highlighted in bold for further distinction. A Welch's t-test conducted across all sample years reveals that the mean values of the overall ESG score are significantly different from both the E and G pillar scores at the 5% significance level. This finding validates the rationale for disaggregating ESG into its components, highlighting the importance of examining each pillar separately rather than relying solely on the composite ESG metric. Notably, the E pillar consistently reports substantially lower mean values compared to the overall ESG scores, indicating that Australian firms tend to underperform on environmental dimensions. This underperformance may reflect structural challenges in high-emission sectors or a lag in environmental initiatives relative to broader ESG reporting. Conversely, the G pillar exhibits consistently higher mean scores than the overall ESG measure. This pattern likely reflects strong corporate governance frameworks in Australia, supported by regulatory oversight, board accountability, and adherence to governance codes. The S pillar, in contrast, shows the closest alignment with the overall ESG score and is not statistically different from it. This suggests that the social dimension may be the most representative component of the ESG composite score among Australian firms, potentially due to more balanced reporting or consistent stakeholder engagement practices. These distinctions among the ESG dimensions underscore the value of pillar-level analysis and justify the study's focus on disentangling the unique risk implications associated with each ESG component.

Table 1. Overall ESG score and pillar score distribution (2014–2022).

Year	Stat.	ESG	E pillar	S Pillar	G Pillar
2014	Mean	33.55778 ^{EG}	**19.24869**	31.78463	**49.55892**
	Std Dev	19.18888	23.07567	20.14011	22.34596
	Obs	145	145	145	145
2015	Mean	33.92071 ^{EG}	**19.94018**	33.57577	**48.37747**
	Std Dev	18.96661	23.12302	19.78802	22.49133
	Obs	153	153	153	153
2016	Mean	34.29552 ^{EG}	**20.17828**	34.42107	**47.73672**
	Std Dev	18.3918	23.04574	19.44248	21.55996
	Obs	160	160	160	160
2017	Mean	36.15821 ^{EG}	**20.84739**	37.26158	**49.05727**
	Std Dev	18.73255	23.09005	20.0646	21.19597
	Obs	159	159	159	159
2018	Mean	38.0443 ^{EG}	**23.11139**	38.92257	**50.88708**
	Std Dev	19.53788	23.95241	21.62899	21.94425
	Obs	159	159	159	159
2019	Mean	40.71483 ^{EG}	**27.13019**	42.00445	**51.78322**
	Std Dev	19.74572	24.47429	21.67382	21.5308
	Obs	161	161	161	161
2020	Mean	43.0121 ^{EG}	**30.41057**	44.93405	**52.18841**
	Std Dev	20.05927	24.7509	21.65854	22.02869
	Obs	158	158	158	158
2021	Mean	44.82225 ^{EG}	**33.24627**	47.48578	**52.04646**
	Std Dev	20.5408	24.79012	22.10155	22.76037
	Obs	157	157	157	157
2022	Mean	45.36306 ^{EG}	**34.30308**	47.80923	**52.17197**
	Std Dev	20.27662	24.55367	22.55134	22.20251
	Obs	160	160	160	160
All	Mean	38.94293 ^{EG}	25.45387	39.89629	50.43803
	Total Obs	1412	1412	1412	1412

Notes: Superscripts 'E' and 'G' indicate that the overall ESG mean score is significantly different from the E and G pillar mean scores at the 5% significance level.

4.2.2. Dependent Variables: Probability of Default

Probability of default, PD, is a financial risk term that is used to describe the likelihood of a firm's default over a particular time. The dependent variable in this study is the PD. CRI estimates firm-level PDs over multiple horizons using a proprietary hazard-based logit model. This model is designed to predict the likelihood that a firm will default on its obligations within a given time frame by linking historical default outcomes to a set of explanatory variables. The CRI model incorporates firm-specific accounting data (e.g., leverage, profitability, liquidity ratios); market-based indicators (e.g., stock return volatility, market capitalization changes); and macroeconomic conditions (e.g., interest rates). The model is calibrated on a global training dataset covering thousands of firms across both developed and emerging markets, allowing for consistent cross-country comparability. While this paper focuses exclusively on Australian-listed non-financial firms, the PDs are generated using the globally calibrated CRI model parameters. Importantly, ESG scores, whether overall or at the E, S, or G pillar level, are not included as explanatory variables in the CRI model. This ensures that the PDs used in this study are determined independently of ESG inputs. Consequently, our research examines the association between ESG performance and default probabilities derived from an external, ESG-neutral credit risk model. Following (H. Li et al., 2022), we consider 1-month PD (PD1) for short-term risk, 6-month PD (PD6) for medium risk, and 12-month PD (PD12) to measure long-term default risk. We select the PD scores in December every year, as they provide the most comprehensive snapshot of a firm's credit risk for that year. Additionally, it may capture seasonal effects, improve accuracy, and consistency.

Figure 1 presents the yearly evolution of PD1, PD6, and PD12 for Australian-listed firms from 2014 to 2022. From the Australian market perspective, the graph reveals several significant trends. Across the period, PD12 consistently shows higher values compared to PD6 and PD1, indicating that long-term credit risk is a more prominent concern in the Australian corporate sector. This is particularly evident in 2015 and 2020, where PD12 spikes significantly. The 2015 spike can be attributed to the commodity price slump, which adversely affected resource-heavy Australian sectors such as mining and energy, key components of the ASX. The 2020 peak coincided with the onset of the COVID-19 pandemic, which led to significant market disruption, particularly for sectors heavily reliant on global supply chains, travel, and consumer spending. There is a notable dip in PD values in 2021, particularly for PD12. This likely reflects government fiscal support, record-low interest rates, and regulatory forbearance measures during the COVID-19 pandemic, which temporarily reduced perceived credit risk. The moderate rebound in 2022 suggests growing awareness of inflationary pressure, rising interest rates, and post-pandemic debt overhang concerns among investors and creditors. PD6 follows a smoother but still responsive trajectory, indicating that mid-range financial uncertainty reacts predictably to macroeconomic and policy events. The upward trend from 2017 to 2020 parallels both climate policy debates and trade disruptions, suggesting ESG-related vulnerabilities may also be reflected in this timeframe. The relative stability of PD1 underscores that short-term default risk is less volatile, possibly because most Australian firms maintain sufficient liquidity buffers or access to working capital within a 30-day horizon. However, even small changes in PD1 across years may signal market sensitivity to earnings expectations or liquidity tightening. Overall, these patterns highlight the importance of ESG performance as a factor in firm-level credit risk, particularly in Australia, where regulatory frameworks are strengthening, investors increasingly consider ESG risks in pricing credit and equity securities, and the economy's reliance on carbon-intensive industries amplifies long-term environmental and reputational risk exposure. These findings provide strong motivation to explore whether firms with higher ESG engagement and specifically stronger performance in environmental and social pillars demonstrate greater resilience to macroeconomic shocks, thus reducing their probability of default across various risk horizons.

4.2.3. Control Variables

Referring to previous research (Do & Vo, 2023; H. Li et al., 2022; Maquieira et al., 2024) the control variables chosen includes: leverage ratio (LEV, the ratio of total liabilities to total assets), stock realized volatility (RV), firm size (SZ, the natural logarithm of total assets), market capitalization (MC), return on assets (ROA, the ratio of net profit to total assets), earnings per share (EPS, the profit generated for each outstanding share of common stock), book-to-market ratio (BM, the ratio of book value of equity to market capitalization).

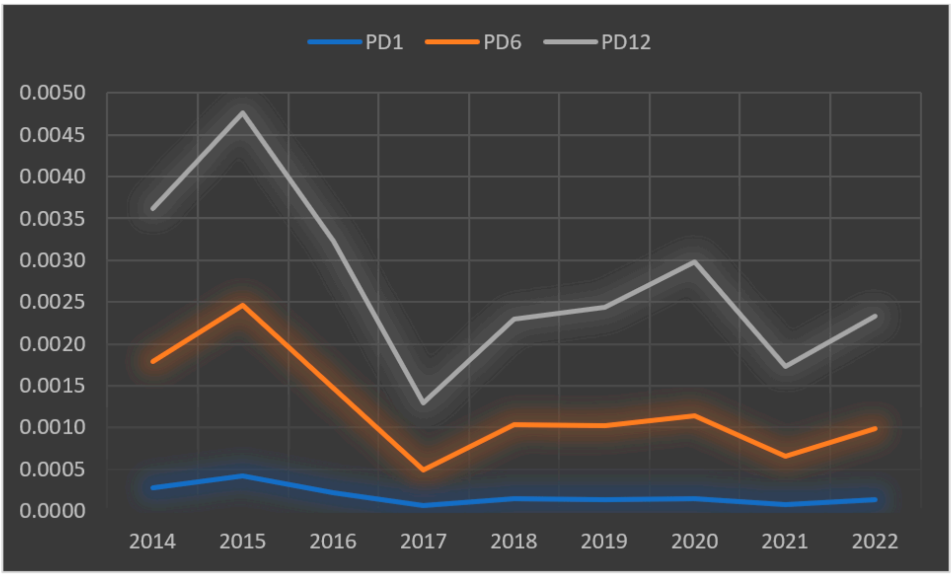

Figure 1. Evolution of mean probability of default (PD): Australian Firms (2014–2022).

4.2.4. Mediating Variable: Trade Credit Financing (TCF)

The mediating variable in this study is trade credit financing (TCF). TCF is the ratio of the sum of accounts receivable, accounts payable, and notes payable divided by total assets.

4.3. Empirical Model

The baseline regression model used to empirically test H1 and H2 is specified as

$$PD_{i,1,6,12} = \beta 0 + \beta 1 EX_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{1}$$

In this model:

- $PD_{i,1,6,12}$ PD_i denotes the probability of default of firm i at three periods: short-term 1-month, medium 6-month, and long-term 12-month, serving as the dependent variable (firm risk).
- $\sum Control_{i,t}$ represents the set of control variables
- $EX_{i,t}$ is the main explanatory variable, which varies based on the hypothesis being tested:

For H1: $EX_{i,t}$ denotes the ESG overall score, used to investigate whether ESG overall performance is related to a firm's probability of default.

For H2: $EX_{i,t}$ represents E, S, and G pillar scores, respectively, to examine whether each pillar has an impact on a firm's probability of default.

To test H3, which determines the mediating role of TCF, the study establishes Equations (2) and (3)

$$TCF_{i,t} = \beta 0 + \beta 1 EX_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$PD_{i,1,6,12} = \beta 0 + \beta 1 EX_{i,t} + \beta 2\, TCF_{i,t} + \sum Control_{i,t} + \varepsilon_{i,t} \tag{3}$$

In both equations, $EX_{i,t}$ represents either the ESG overall score or individual pillars (E, S, or G). Together, these equations are used to test whether ESG performance reduces firm risk through its effect on TCF, thereby validating a partial mediation effect.

4.4. Method and Model Robustness

To identify initial patterns and characteristics, this study first calculates the descriptive statistics for all variables. Its next focuses on the relationship between PD and the overall ESG score as well as its individual E, S, and G pillars. Then, establish a Pearson correlation matrix to measure linear relationships between each ESG dimension and PD at a single period.

The two-step system, Generalized Method of Moments (GMM) technique, created by Arellano and Bover (1995) and Blundell and Bond (1998), is used in this study to estimate dynamic relationships and address any endogeneity issues. Since GMM successfully handles a variety of endogeneity types, such as simultaneity, omitted variables, and dynamic relationships, it is especially well-suited for dynamic panel data (Ullah et al., 2018; Roodman, 2009). Furthermore, heteroskedasticity and autocorrelation problems are recognized to be handled by GMM (Haris et al., 2019; Anatolyev, 2005).

To account for any lagged impacts, a one-period lag of the ESG variables, both overall and for individual pillars, is added. Additionally, the study splits the entire sample into two groups to further support the robustness of the baseline model estimations. The first group includes firms associated with the industrial sector, while the other comprises the remaining companies.

5. Empirical Analysis and Findings

5.1. Descriptive Statistics and Correlation

Table 2 reports the descriptive statistics of the key variables used in this study. The probability of default measures, PD1, PD6, and PD12, exhibit a notably skewed distribution. While their means are relatively low (0.000179, 0.0012161, and 0.0027221, respectively), the corresponding maximum values (0.01872, 0.086032, and 0.129957) suggest that a subset of firms experience elevated default risk episodes, possibly driven by firm-specific or sectoral vulnerabilities. This pattern underscores the significance of assessing firm-level risk factors, particularly the impact of ESG performance on mitigating credit risk exposures.

Table 2. Descriptive statistics of the variables.

Variables	Obs.	Mean	Std. Dev.	Min	Max
		Dependent variables			
PD1	1412	0.000179	0.0007987	0	0.01872
PD6	1412	0.0012161	0.004222	0	0.086032
PD12	1412	0.0027221	0.007372	0	0.129957
		Independent variables			
ESG	1412	38.94293	19.95768	2.361009	90.21835
E pillar	1412	25.45387	24.49137	0	89.48721
S pillar	1412	39.89629	21.74066	1.673614	96.21201
G pillar	1412	50.43803	22.00528	2.150012	97.90799
		Control variables			
EPS	1402	0.3022826	0.9289128	−5.5209	6.981645
RV	1408	0.5047252	0.2891519	0.0526412	2.890167
MC	1411	5278.353	17993.92	0.00128	330153.3
LEV	1411	0.424435	0.2684662	0.0070155	4.304998
SZ	1411	6.711351	1.969042	0.6570017	11.99585
ROA	1410	−0.0229349	0.2395173	−2.797904	0.527159
BM	1411	11.64171	148.7891	−4.833585	3250.781

The data also reveal substantial variation in firms' financial performance. The mean return on assets (ROA) is negative (−0.0229349), and the minimum value reaches as low as −2.797904, indicating that many firms within the sample face profitability challenges. This raises important questions about whether ESG practices can help alleviate the operational uncertainty associated with weak financial performance.

In terms of capital structure, the mean leverage ratio stands at 0.424435, suggesting a moderately geared profile for most firms. However, the maximum leverage value (4.304998) indicates that certain firms, likely operating in capital-intensive industries, maintain significantly higher debt levels. These firms may be more sensitive to risk shocks and could potentially benefit more from strong ESG practices as a stabilizing force.

Collectively, these descriptive statistics provide strong motivation to explore further whether ESG performance and its dimensions of E, S, and G play a protective role against firm-specific credit risk, as proxied by varying term structures of default probability.

The significant coefficients, indicating the degrees of Pearson correlation between the variables in the regression model, are displayed in Table 3. This correlation-based finding supports a more thorough examination (for example, using regression analysis) of the relationship between ESG performance and default risk, particularly after adjusting for other firm-specific factors.

Table 3. Pearson correlations.

	PD1	PD6	PD12	ESG	E Pillar	S Pillar	G Pillar	EPS	RV	MC	LEV	SZ	ROA	BM
PD1	1.000													
PD6		1.000												
PD12			1.000											
ESG	−0.1113 *	−0.1209 *	−0.1281 *	1.000										
E pillar	−0.0786 *	−0.0833 *	−0.0861 *		1.000									
S pillar	−0.0966 *	−0.1047 *	−0.1108 *			1.000								
G pillar	−0.0890 *	−0.0989 *	−0.1075 *				1.000							
EPS	−0.1061 *	−0.1295 *	−0.1545 *	0.3397 *	0.2752 *	0.3486 *	0.2226 *	1.000						
RV	0.3549 *	0.3796 *	0.4049 *	−0.4056 *	−0.3317 *	−0.3321 *	−0.3586 *	−0.2779 *	1.000					
MC	−0.0548 *	−0.0662 *	−0.0778 *	0.4341 *	0.3874 *	0.4224 *	0.3194 *	0.4767 *	−0.1980 *	1.000				
LEV	0.2097 *	0.2406 *	0.2728 *	0.1769 *	0.1628 *	0.1570 *	0.1347 *	0.0176	−0.0368	0.0423	1.000			
SZ	−0.1039 *	−0.1075 *	−0.1066 *	0.7322 *	0.7002 *	0.6398 *	0.5841 *	0.3292 *	−0.5671 *	0.4594 *	0.2126 *	1.000		
ROA	−0.1910 *	−0.2075 *	−0.2209 *	0.2639 *	0.2299 *	0.1996 *	0.2355 *	0.2984 *	−0.4951 *	0.1268 *	0.0236	0.4501 *	1.000	
BM	0.0498	0.0537 *	0.0590 *	−0.0977 *	−0.0701 *	−0.1112 *	−0.0441	−0.0251	0.1843 *	−0.0221	−0.0412	−0.1436 *	−0.0634 *	1.000

Notes: * represents statistical significance at 10%.

5.2. Regression Analysis

5.2.1. Impact of Overall ESG and Pillars (E, S, G) on the Firm's Probability of Default

The estimation outcomes of the two-step system GMM technique applied to the empirical models specified in Equation (1) are displayed in Table 4. The results for Hypothesis 1 are shown in the "ESG" column of Table 4. The pillar-specific findings relevant to Hypothesis 2 are shown in the remaining columns. The outputs that are given contain the estimated coefficients. Standard errors are displayed in parentheses beneath each coefficient. The Hansen J test for instrument validity and the AR(2) test for second-order serial correlation both exhibit negligible p-values, indicating that all models are statistically valid. The findings reveal that the overall ESG score, along with the E and S pillars, is consistently associated with a significant reduction in default risk across all horizons. In contrast, the G pillar exhibits a positive and statistically significant association with default probabilities at all horizons. Turning to the control variables, several well-established predictors of default risk emerge. Realized volatility and leverage are strongly positive, confirming their roles as major drivers of financial fragility. Firm size and profitability generally reduce default risk, while earnings per share exhibit a consistent negative influence, reinforcing the protective role of financial strength.

Table 4. Impact of ESG overall and individual pillar on the firm's probability of default.

Variables	ESG			E Pillar			S Pillar			G Pillar		
	PD1	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**
(ESG/pillars)	-7.98×10^{-6} *** (0.0000013)	−0.0000479 *** (0.0000141)	−0.0000971 ** (0.0000463)	-8.52×10^{-6} *** (0.0000016)	−0.0000407 ** (0.0000167)	−0.0000919 ** (0.00004)	-8.56×10^{-6} *** (0.0000014)	−0.0000433 *** (0.0000069)	−0.0000687 * (0.0000403)	0.0000127 *** (0.0000036)	0.0000466 *** (0.0000062)	0.0000831 *** (0.0000198)
EPS	−0.0000791 ** (0.0000339)	−0.0001581 (0.0001916)	−0.0002948 (0.0005834)	−0.0000827 *** (0.0000291)	−0.0001718 ** (0.0002809)	−0.0003267 (0.0005513)	−0.0000642 * (0.0000343)	−0.0002848 (0.0001763)	−0.00018 (0.0006047)	−0.0000237 (0.0000941)	−0.0003579 (0.0003063)	−0.0005532 (0.0004637)
RV	0.0027727 *** (0.0001971)	0.0080394 *** (0.0015302)	0.0200553 *** (0.0053749)	0.0027754 *** (0.0002103)	0.0182962 *** (0.0023956)	0.0189913 *** (0.0064978)	0.0026468 *** (0.0001982)	0.0130787 *** (0.0008444)	0.0184597 *** (0.0054305)	−0.001312 * (0.0007637)	0.0088671 ** (0.0037799)	0.0262989 *** (0.0035055)
MC	2.86×10^{-10} (0.0000000)	-1.16×10^{-9} (0.0000000)	-1.50×10^{-9} (0.0000000)	-1.10×10^{-10} (0.0000000)	-6.38×10^{-9} (0.0000000)	-3.73×10^{-9} (0.0000000)	7.09×10^{-11} (0.0000000)	-9.35×10^{-10} (0.0000000)	-2.79×10^{-9} (0.0000000)	3.49×10^{-9} (0.0000000)	2.71×10^{-9} (0.0000000)	-6.21×10^{-9} (0.0000000)
LEV	0.0004819 *** (0.0000805)	0.002339 *** (0.0004751)	0.0056047 *** (0.0014825)	0.0005416 *** (0.0000783)	0.0020651 ** (0.0008074)	0.0056437 *** (0.0016541)	0.0005238 *** (0.0000767)	0.003172 *** (0.0003615)	0.0056648 *** (0.001476)	0.0004711 ** (0.0002168)	0.0021638 *** (0.0007695)	0.0041906 *** (0.0011401)
SZ	0.0001712 *** (0.0000207)	0.0007016 *** (0.0001499)	0.0018268 *** (0.0005554)	0.0001985 *** (0.0000236)	0.0013327 *** (0.0003031)	0.001783 ** (0.0006831)	0.0001729 *** (0.0000214)	0.0008738 *** (0.0000946)	0.0015944 *** (0.0005802)	−0.000093 (0.0000595)	0.0001916 (0.0002275)	0.0009177 *** (0.0002961)
ROA	0.0011431 *** (0.0001838)	0.0016091 (0.0017082)	0.001718 (0.0081515)	0.0011352 *** (0.0001803)	0.0037491 (0.0035417)	0.0020912 (0.0088292)	0.0009859 *** (0.0001638)	0.0039003 *** (0.0008545)	0.000105 (0.0079839)	−0.0025392 (0.0016463)	0.0009662 (0.0038488)	0.0054695 (0.0051202)
BM	7.97×10^{-7} *** (4.74×10^{-8})	2.30×10^{-7} (2.81×10^{-6})	−0.0000127 * (6.74×10^{-6})	8.72×10^{-7} *** (5.11×10^{-8})	2.73×10^{-6} *** (6.14×10^{-7})	−0.0000137 * (7.45×10^{-6})	8.65×10^{-7} *** (4.54×10^{-8})	3.59×10^{-6} *** (1.93×10^{-7})	−0.0000132 * (7.23×10^{-6})	4.43×10^{-7} * (2.32×10^{-7})	8.81×10^{-7} (1.16×10^{-6})	4.47×10^{-6} *** (1.40×10^{-6})
Cons	−0.002206 *** (0.0001957)	−0.0066576 *** (0.0013451)	−0.0182664 *** (0.0049248)	−0.002518 *** (0.0002084)	−0.016702 *** (0.0025778)	−0.0188594 *** (0.0063613)	−0.0021535 *** (0.0001983)	−0.0106933 *** (0.0008294)	−0.0170376 *** (0.0050373)	0.0005211 (0.0006366)	−0.0079708 ** (0.0031076)	−0.0227457 *** (0.0029714)
Obs.	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398
AR (2)	0.552 (0.59)	0.277 (−1.09)	0.427 (−0.79)	0.528 (0.63)	0.358 (0.92)	0.344 (−0.95)	0.592 (0.54)	0.856 (0.18)	0.350 (−0.93)	0.526 (−0.63)	0.622 (−0.49)	0.413 (0.82)
Hansen	0.164 (47.53)	0.852 (25.53)	0.305 (13.94)	0.334 (42.20)	0.500 (20.34)	0.575 (10.47)	0.202 (46.10)	0.133 (48.92)	0.295 (14.10)	0.996 (2.88)	0.627 (18.34)	0.161 (27.31)
Model efficacy	√	√	√	√	√	√	√	√	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively. √ indicates models are valid.

5.2.2. Mediating Role of TCF on ESG-Firm's Probability of Default

Table 5 presents the GMM regression results of the association between ESG and trade credit financing, proxied by TCF. Each column (ESG, E pillar, S pillar, G pillar) denotes the independent variable, with TCF as the dependent variable (Equation (2)). The results indicate that overall ESG scores are significantly and negatively associated with TCF, suggesting that firms with stronger sustainability profiles rely less on trade credit. This pattern holds consistently across the E, S, and G pillars, with the effect being strongest for G. Among the control variables, leverage is positively and strongly related to TCF across all specifications, highlighting that more indebted firms tend to rely more heavily on trade credit. Profitability (ROA) also shows a positive and significant impact on TCF, suggesting that financially stronger firms may use trade credit strategically despite having internal resources. Conversely, the book-to-market ratio (BM) is negatively significant, indicating that firms with higher growth opportunities are less reliant on supplier credit. Firm size and volatility do not exhibit consistent significance, implying that these factors play a limited role in trade credit usage in this context. The diagnostic tests (AR (2) and Hansen J-statistics) confirm the validity of the GMM specifications, ensuring robustness of the results.

Table 5. Impact of ESG overall and individual pillar on trade credit financing.

Dep. Variable	Indep. Variable	ESG	E Pillar	S Pillar	G Pillar
TCF	ESG/pillars	−0.0022883 ** (0.0009423)	−0.000989 * (0.0005294)	−0.0012342 * (0.0006982)	−0.0035127 *** (0.0011211)
	EPS	0.011415 (0.0169303)	−0.0001964 (0.0184657)	0.0032576 (0.0120565)	0.0049266 (0.0172319)
	RV	0.0180593 (0.0792938)	0.0133665 (0.0664787)	0.0085429 (0.0534541)	−0.0100346 (0.0993587)
	MC	-4.72×10^{-7} (6.08×10^{-7})	-3.09×10^{-7} (8.04×10^{-7})	-2.39×10^{-7} (5.31×10^{-7})	-4.99×10^{-7} (6.10×10^{-7})
	LEV	0.2228779 *** (0.0512151)	0.1680504 *** (0.0439766)	0.1663953 *** (0.0539653)	0.1568942 *** (0.0546842)
	SZ	−0.0133857 (0.0139861)	−0.0032478 (0.0113602)	−0.0151677 (0.0121903)	−0.0054517 (0.010672)
	ROA	0.6291598 *** (0.1631774)	0.3062646 * (0.1725961)	0.495529 *** (0.1752388)	0.5998348 ** (0.2964818)
	BM	−0.0000904 *** (0.0000266)	−0.000067 (0.0000445)	−0.0000701 *** (0.0000212)	−0.0000889 ** (0.0000394)
	Cons	0.2293302 ** (0.1034095)	0.1111323 (0.0790219)	0.2291603 *** (0.0829705)	0.3063543 *** (0.1040927)
	Obs.	1398	1398	1398	1398
	AR(2) Stat.	0.332 (−0.97)	0.108 (−1.61)	0.268 (−1.11)	0.277 (−1.09)
	Hansen J Stat.	0.922 (5.87)	0.434 (10.07)	0.832 (5.80)	0.973 (3.32)
	Model efficacy	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1% level, respectively. √ indicates models are valid.

Table 6 presents the GMM regression results, where TCF serves as a mediating variable between ESG and PD, as per Equation (3). These associations are related to Hypothesis 3. Table 6 shows that overall ESG, along with the E and S pillars, has a consistently negative and significant effect on default probability across the 1-, 6-, and 12-month horizons, indicating that firms with stronger ESG, E, and S performance face lower default risk. In contrast, the G pillar has a positive and significant association with default probability, suggesting that higher G scores are linked to increased default risk. TCF is positive and significant in all models, meaning greater reliance on TCF increases the likelihood of default. Since ESG (as shown in Table 5) reduces TCF reliance, part of ESG's risk-lowering effect works indirectly through this channel. Among control variables, RV and LEV both raise default risk, while SZ generally lowers it, particularly at longer horizons. Profitability (ROA) strongly reduces default risk, whereas BM effects are mixed, with only small and occasionally significant coefficients.

5.3. Robustness Tests

5.3.1. One-Period Lagged Explanatory Variable

The research can be made more robust by examining whether the effects of ESG and its pillars on risk are consistent over time. Therefore, this study used a one-period lag of the explanatory variables, which are the ESG overall score and its pillar (E, S, and G), to re-estimate the baseline models. Equation (1) was explicitly used to re-specify the models, substituting the one-period lagged ESG variables (L1.ESG/Pillars) for the contemporaneous ones. The dynamic system GMM technique was used for the estimation. Table 7 describes the findings. According to the findings of the negligible AR(2) and Hansen tests, the diagnostic tests shown in the table indicate that all models using lagged ESG and pillar scores are statistically valid.

5.3.2. Two Samples of Explanatory Variable

Another robust check was performed by dividing the entire sample into two groups. The first group includes industrial firms, and the second one comprises the rest of the companies. Table 8 shows the result of estimation following the baseline model at Equation (1) with a sample that contains non-industrial firms. Regarding the findings of Table 8, the diagnostic tests reported indicate that all models incorporating ESG overall and single pillar scores are statistically valid since they have insignificant AR (2) and Hansen test results. Table 9 presents the regression results for the industrial company's sample.

Table 6. Mediating role of trade credit financing in the relationship between ESG and the probability of default.

Variables	ESG			E Pillar			S Pillar			G Pillar		
	PD1	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**
(ESG/ pillars)	-4.68×10^{-6} *** (1.46×10^{-6})	−0.0000232 *** (8.45×10^{-6})	−0.0000372 ** (0.0000164)	-3.27×10^{-6} ** (1.35×10^{-6})	−0.0000216 *** (6.52×10^{-6})	−0.000038 *** (0.0000121)	-3.34×10^{-6} *** (1.19×10^{-6})	−0.000016 ** (6.12×10^{-6})	−0.0000268 ** (0.000012)	0.0000169 *** (5.04×10^{-6})	0.0000895 ** (0.000037)	0.0001471 * (0.0000862)
TCF	0.0017314 *** (0.0003697)	0.0079883 *** (0.0021486)	0.011506 *** (0.0039979)	0.0009852 ** (0.0004594)	0.0068831 *** (0.002185)	0.0101955 ** (0.0040094)	0.0010806 ** (0.0004909)	0.0076946 *** (0.0023026)	0.011833 *** (0.0042279)	0.0018418 * (0.0010781)	0.0116658 * (0.0064263)	0.0237188 * (0.0128344)
EPS	3.24×10^{-6} (0.000015)	−0.000033 (0.0000939)	−0.0001662 (0.0001879)	9.91×10^{-7} (0.0000155)	-9.06×10^{-6} (0.0000886)	−0.0001326 (0.0001727)	-7.77×10^{-7} (0.0000154)	−0.0000266 (0.0000913)	−0.0001355 (0.0001824)	−0.000014 (0.0000745)	2.55×10^{-7} (0.0004377)	−0.0006293 (0.0019488)
RV	0.0009066 *** (0.0000774)	0.0048753 *** (0.0004254)	0.0085606 *** (0.0008511)	0.0007729 *** (0.0001006)	0.0048684 *** (0.0004293)	0.008901 *** (0.0008339)	0.0007957 *** (0.0000973)	0.0049799 *** (0.0004326)	0.0088941 *** (0.0008462)	−0.0011401 * (0.000657)	−0.0060201 * (0.0034586)	−0.0115215 (0.0072487)
MC	1.28×10^{-10} (5.19×10^{-10})	9.54×10^{-10} (2.94×10^{-9})	1.04×10^{-9} (5.40×10^{-9})	-2.72×10^{-10} (5.36×10^{-10})	-3.28×10^{-10} (2.76×10^{-9})	-1.20×10^{-9} (5.11×10^{-9})	5.34e−12 (5.92×10^{-10})	1.41×10^{-9} (2.93×10^{-9})	1.54×10^{-9} (5.27×10^{-9})	3.64×10^{-9} (2.70×10^{-9})	1.78×10^{-8} (1.43×10^{-8})	1.39×10^{-7} (1.98×10^{-7})
LEV	0.0002418 *** (0.0000421)	0.0018203 *** (0.000252)	0.0042887 *** (0.0004982)	0.0002366 *** (0.0000469)	0.0019237 *** (0.0002467)	0.0043761 *** (0.0004773)	0.0002206 *** (0.0000471)	0.0017332 *** (0.0002461)	0.0040562 *** (0.0004856)	0.0003113 * (0.000178)	0.002223 ** (0.0010023)	0.0044082 ** (0.0020036)
SZ	0.0000774 *** (0.0000161)	0.0003815 *** (0.000091)	0.0006325 *** (0.0001675)	0.000063 *** (0.0000191)	0.0003903 *** (0.0000902)	0.0006858 *** (0.000165)	0.0000556 *** (0.0000152)	0.000324 *** (0.0000736)	0.0005717 *** (0.0001359)	−0.0001134 *** (0.0000401)	−0.0006253 ** (0.0002943)	−0.0012862 (0.0008181)
ROA	−0.0005341 *** (0.0000816)	−0.0028297 *** (0.0004781)	−0.0047502 *** (0.0009346)	−0.000372 *** (0.0000988)	−0.0026071 *** (0.0004594)	−0.0043906 *** (0.0009039)	−0.0003858 *** (0.0000982)	−0.0027359 *** (0.0004723)	−0.004759 *** (0.0009156)	−0.0028485 ** (0.0012502)	−0.015357 ** (0.0069242)	−0.0310998 ** (0.0145516)
BM	-5.16×10^{-7} * (2.99×10^{-7})	-7.77×10^{-7} (1.48×10^{-6})	2.31×10^{-6} (2.60×10^{-6})	-3.71×10^{-7} (3.55×10^{-7})	-2.22×10^{-6} (1.57×10^{-6})	-9.50×10^{-8} (2.94×10^{-6})	-3.86×10^{-7} (3.88×10^{-7})	-1.68×10^{-6} (1.59×10^{-6})	2.63×10^{-7} (2.84×10^{-6})	4.75×10^{-7} ** (1.88×10^{-7})	2.66×10^{-6} ** (1.02×10^{-6})	5.37×10^{-6} ** (2.11×10^{-6})
Cons	−0.000995 *** (0.0000998)	−0.0050788 *** (0.0005625)	−0.0084874 *** (0.0010454)	−0.0008363 *** (0.0001469)	−0.0053526 *** (0.0006344)	−0.0092893 *** (0.0011674)	−0.0007536 *** (0.0001315)	−0.0049657 *** (0.0005568)	−0.0086114 *** (0.001022)	0.000169 (0.0005945)	0.0008093 (0.0033224)	0.0030833 (0.007604)
Obs.	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398	1398
AR (2)	0.209 (−1.26)	0.169 (−1.37)	0.139 (−1.48)	0.182 (−1.34)	0.157 (−1.41)	0.136 (−1.49)	0.182 (−1.33)	0.158 (−1.41)	0.134 (−1.50)	0.509 (−0.66)	0.462 (−0.74)	0.471 (−0.72)
Hansen	0.391 (49.05)	0.397 (48.89)	0.325 (50.84)	0.536 (36.57)	0.321 (50.94)	0.222 (54.11)	0.532 (36.66)	0.311 (51.23)	0.234 (53.67)	1.000 (1.49)	1.000 (2.20)	0.999 (1.93)
Model efficacy	√	√	√	√	√	√	√	√	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively. √ indicates models are valid.

Table 7. Impact of one-period lagged ESG overall score and its individual pillar (E, S, G) on a firm's probability of default.

Variables	L1.ESG			L1.E Pillar			L1.S Pillar			L1.G Pillar		
	PD1	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**
(L1. ESG/ pillars)	−0.0000114 *** (1.45×10^{-6})	−0.0000523 *** (6.78×10^{-6})	−0.0000748 *** (0.0000108)	-3.04×10^{-6} *** (8.74×10^{-7})	−0.0000176 *** (5.69×10^{-6})	−0.0000679 * (0.0000356)	-2.51×10^{-6} ** (1.23×10^{-6})	−0.0000351 ** (0.0000169)	−0.0000633 * (0.0000333)	4.03×10^{-6} *** (3.35×10^{-7})	0.0000225 *** (2.08×10^{-6})	0.0001202 *** (0.0000255)
EPS	−0.0000633 * (0.0000368)	−0.0002783 (0.0001743)	−0.000356 (0.0003164)	0.0000224 * (0.0000123)	0.0001048 (0.0000776)	−0.0002696 (0.0005314)	0.0000127 (0.0000166)	0.0006175 (0.0005561)	0.0010115 (0.0011602)	0.0000163 (0.0000118)	0.0000946 (0.0000724)	0.0001003 (0.0007057)
RV	0.002795 *** (0.000201)	0.0137608 *** (0.000852)	0.0222625 *** (0.0011987)	0.0006042 *** (0.0000455)	0.0035022 *** (0.0002532)	0.0182684 *** (0.0065437)	0.0003505 *** (0.0001027)	0.0047085 *** (0.0015989)	0.0094646 *** (0.0031229)	0.0006623 *** (0.0000409)	0.0037634 *** (0.0002363)	0.003184 (0.0029199)
MC	5.14×10^{-10} (8.78×10^{-10})	1.71×10^{-9} (3.86×10^{-9})	-2.63×10^{-10} (6.33×10^{-9})	-8.82×10^{-10} *** (2.84×10^{-10})	-6.97×10^{-9} *** (1.82×10^{-9})	-4.48×10^{-9} (1.76×10^{-8})	-3.31×10^{-10} (5.87×10^{-10})	-2.39×10^{-8} (2.06×10^{-8})	-4.08×10^{-8} (4.38×10^{-8})	-9.07×10^{-10} *** (3.28×10^{-10})	-5.55×10^{-9} *** (2.00×10^{-9})	-1.03×10^{-8} (2.55×10^{-8})
LEV	0.0004846 *** (0.0000751)	0.0029905 *** (0.0003586)	0.0060158 *** (0.0005549)	0.0002847 *** (0.0000493)	0.0020697 *** (0.0002676)	0.0048094 *** (0.0016228)	0.000261 *** (0.0000704)	0.0031118 *** (0.0008197)	0.0064232 *** (0.0015181)	0.0003159 *** (0.0000357)	0.002118 *** (0.0002044)	0.0071583 *** (0.0012591)
SZ	0.0001979 *** (0.0000213)	0.0009545 *** (0.0000939)	0.0015097 *** (0.0001381)	0.0000561 *** (7.63×10^{-6})	0.0003494 *** (0.0000468)	0.001658 ** (0.0006808)	0.0000305 ** (0.0000154)	0.0003392 (0.0002178)	0.0007301 * (0.0004354)	-7.24×10^{-6} (4.74×10^{-6})	−0.000035 (0.0000291)	−0.0015437 *** (0.0004836)
ROA	0.0011008 *** (0.0001711)	0.0047178 *** (0.0008598)	0.0066022 *** (0.0014319)	−0.0004153 *** (0.0000796)	−0.0026229 *** (0.0004749)	0.0004188 (0.0084355)	−0.0002841 * (0.0001441)	0.0013484 (0.0015436)	0.0017677 (0.003495)	−0.0003149 *** (0.000078)	−0.0020281 *** (0.0004784)	0.0110583 (0.0074548)
BM	7.99×10^{-7} *** (4.30×10^{-8})	3.33×10^{-6} *** (1.90×10^{-7})	4.80×10^{-6} *** (2.89×10^{-7})	7.81×10^{-8} *** (1.14×10^{-8})	6.45×10^{-7} *** (6.62×10^{-8})	−0.0000133 * (7.41×10^{-6})	3.94×10^{-8} (2.66×10^{-8})	7.87×10^{-8} (3.56×10^{-7})	4.83×10^{-7} (7.51×10^{-7})	5.77×10^{-9} (9.10×10^{-9})	2.10×10^{-7} *** (5.45×10^{-8})	1.66×10^{-7} (8.41×10^{-7})
Cons	−0.0023091 *** (0.0002051)	−0.0113612 *** (0.0008612)	−0.0184065 *** (0.0012045)	−0.0006177 *** (0.0000576)	−0.0037568 *** (0.0003177)	−0.0182115 *** (0.0063463)	−0.0002909 *** (0.0001092)	−0.0036907 ** (0.0016603)	−0.0077417 ** (0.0032728)	−0.0004979 *** (0.0000541)	−0.0028144 *** (0.0003141)	0.0020161 (0.0036656)
Obs.	1234	1234	1234	1234	1234	1234	1234	1234	1234	1234	1234	1234
AR (2)	0.338 (0.96)	0.425 (0.80)	0.428 (0.79)	0.265 (−1.11)	0.289 (−1.06)	0.769 (−0.29)	0.227 (−1.21)	0.416 (−0.81)	0.569 (−0.57)	0.231 (−1.20)	0.260 (−1.13)	0.727 (−0.35)
Hansen	0.322 (42.51)	0.214 (45.70)	0.173 (47.16)	0.759 (24.29)	0.545 (28.48)	0.657 (9.54)	0.151 (16.96)	0.873 (6.76)	0.856 (7.02)	0.110 (50.06)	0.158 (47.79)	0.590 (18.92)
Model efficacy	√	√	√	√	√	√	√	√	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively. √ indicates models are valid.

Table 8. Impact of ESG overall score and its individual pillar (E, S, G) on non-industrial firms' probability of default.

Variables (Non-Industrial Firms)	ESG			E Pillar			S Pillar			G Pillar		
	PD1	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**
(ESG/pillars)	-9.48×10^{-6} * (5.36×10^{-6})	−0.00006 * (0.0000358)	−0.0001161 * (0.0000692)	-1.04×10^{-6} * (6.21×10^{-7})	-5.95×10^{-6} ** (2.92×10^{-6})	−0.0000518 * (0.0000304)	-1.10×10^{-6} ** (4.69×10^{-7})	−0.0000114 *** (3.94×10^{-6})	−0.0000258 *** (9.10×10^{-6})	2.17×10^{-6} ** (1.02×10^{-6})	0.0000149 ** (6.92×10^{-6})	0.0000159 *** (4.27×10^{-6})
EPS	0.000228 (0.0001402)	0.0015998 * (0.0008943)	0.003167 * (0.0016495)	0.0000102 (0.0000119)	−0.0000609 (0.0000846)	0.0025263 (0.0018924)	-9.15×10^{-6} (0.0000166)	−0.0001531 (0.0001296)	−0.0004572 (0.0003108)	−0.0000328 ** (0.000016)	−0.000169 (0.0001145)	−0.0000862 (0.0000994)
RV	0.000338 (0.0004307)	0.00158 (0.0026868)	0.0017826 (0.005176)	0.0002064 *** (0.0000394)	0.0032638 *** (0.000406)	0.0009058 (0.0027832)	0.0003468 *** (0.0000625)	0.0029658 *** (0.0009489)	0.0063303 *** (0.0021133)	0.0001894 *** (0.000068)	0.001367 ** (0.0005311)	0.0042611 *** (0.0003409)
MC	-6.85×10^{-9} (6.02×10^{-9})	-4.95×10^{-8} (3.92×10^{-8})	-1.00×10^{-7} (7.51×10^{-8})	-2.02×10^{-9} (3.06×10^{-9})	-6.99×10^{-9} (7.32×10^{-9})	-1.52×10^{-7} (1.28×10^{-7})	-2.18×10^{-10} (1.27×10^{-9})	4.27×10^{-9} (2.55×10^{-8})	1.31×10^{-8} (5.22×10^{-8})	-3.18×10^{-10} (1.39×10^{-9})	-2.96×10^{-9} (9.46×10^{-9})	2.88×10^{-8} *** (6.06×10^{-9})
LEV	0.0009643 *** (0.0002263)	0.0071177 *** (0.001589)	0.0153829 *** (0.0031464)	0.0004899 *** (0.000067)	0.0012365 *** (0.0003136)	0.0063467 *** (0.0016707)	0.0000829 * (0.0000442)	0.0008777 * (0.0004472)	0.0026932 *** (0.0009185)	0.0001119 * (0.000052)	0.0010487 *** (0.0003365)	0.007565 *** (0.0008153)
SZ	0.0000521 (0.0000895)	0.0002751 (0.0005686)	0.0003726 (0.0010622)	-1.54×10^{-6} (0.0000118)	0.0002113 *** (0.0000593)	0.0005238 (0.0005485)	0.000034 *** (8.40×10^{-6})	0.0003043 ** (0.0001202)	0.0006228 ** (0.0002479)	8.16×10^{-6} (0.0000107)	0.0000346 (0.0000778)	−0.0003926 *** (0.0000768)
ROA	−0.0011277 (0.0009737)	−0.0076658 (0.0068559)	−0.0136472 (0.0131706)	0.000052 (0.0000416)	0.0008181 *** (0.0002853)	−0.0078308 (0.0077651)	−0.0000661 (0.0000544)	−0.0007982 (0.0006824)	−0.0019743 (0.0014026)	−0.0000363 (0.0000558)	−0.0005902 (0.0003989)	−0.0002654 (0.0002796)
BM	0.0007588 *** (0.0001839)	0.0052978 *** (0.0012069)	0.0104984 *** (0.0022732)	0.0002579 *** (0.0000236)	−0.0000253 (0.0001411)	0.0039863 *** (0.0006238)	−0.000098 *** (0.0000219)	−0.0007288 *** (0.0002529)	−0.0015063 ** (0.0005717)	−0.0001158 *** (0.0000266)	−0.0008086 *** (0.0001975)	0.004845 *** (0.0001257)
Cons	−0.0009667 (0.0006169)	−0.0061371 (0.0038683)	−0.0107036 (0.0073246)	−0.0003428 *** (0.0000601)	−0.0027241 *** (0.0003914)	−0.0067222 ** (0.0032479)	−0.0002604 *** (0.0000469)	−0.0023565 *** (0.0007836)	−0.0048991 *** (0.001693)	−0.0001712 ** (0.0000658)	−0.0011503 ** (0.0004868)	−0.0044899 *** (0.0005888)
Obs.	603	603	603	603	603	603	603	603	603	603	603	603
AR (2)	0.268 (−1.11)	0.191 (−1.31)	0.121 (−1.55)	0.883 (−0.15)	0.298 (1.04)	0.618 (−0.5)	0.717 (0.36)	0.471 (0.72)	0.290 (1.06)	0.926 (0.009)	0.710 (0.37)	0.487 (−0.69)
Hansen	0.914 (4.64)	0.944 (4.07)	0.962 (3.63)	0.351 (28.16)	0.480 (28.72)	0.816 (10.06)	0.325 (23.37)	0.500 (17.34)	0.466 (17.85)	0.352 (22.85)	0.347 (22.95)	0.407 (43.51)
Model efficacy	√	√	√	√			√	√	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively. √ indicates models are valid.

Table 9. Impact of ESG overall score and its individual pillar (E, S, G) on industrial firms' probability of default.

Variables (Industrial Firms)	ESG			E Pillar			S Pillar			G Pillar		
	PD1	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**	**PD1**	**PD6**	**PD12**
(ESG/pillars)	-8.39×10^{-6} *** (1.52×10^{-6})	−0.0000407 *** (0.0000109)	−0.0000547 *** (0.0000118)	−0.0000164 * (8.92×10^{-6})	−0.0000931 ** (0.0000423)	−0.0001705 ** (0.000065)	-7.77×10^{-6} *** (1.40×10^{-6})	−0.000036 *** (8.99×10^{-6})	−0.0000583 *** (0.0000178)	0.0000134 *** (3.00×10^{-6})	0.0000789 *** (0.000025)	0.0000438 ** (0.0000218)
EPS	0.0000119 (0.0000178)	0.0000393 (0.0001158)	-1.19×10^{-6} (0.0002045)	−0.0000583 (0.000093)	−0.0002173 (0.0004249)	−0.0001771 (0.000681)	0.0000152 (0.0000194)	0.0000783 (0.0001254)	−0.0000207 (0.0002345)	0.0000644 (0.0000621)	0.0004847 (0.0003645)	−0.0001786 (0.0002555)
RV	0.0007932 *** (0.0001216)	0.0045763 *** (0.0005928)	0.0122562 *** (0.0007805)	0.0016115 (0.0016681)	0.0108715 (0.0071002)	0.0238416 ** (0.009391)	0.0009177 *** (0.0001177)	0.0050144 *** (0.0005985)	0.0103801 *** (0.0011219)	−0.0011997 ** (0.0005135)	−0.0072595 ** (0.0027959)	0.0113963 *** (0.0009912)
MC	-1.10×10^{-9} (1.40×10^{-9})	-8.96×10^{-9} (6.68×10^{-9})	-1.75×10^{-8} *** (3.83×10^{-9})	1.37×10^{-9} (2.27×10^{-9})	6.39×10^{-9} (1.17×10^{-8})	9.36×10^{-9} (2.13×10^{-8})	-2.17×10^{-9} (1.50×10^{-9})	-1.33×10^{-8} * (7.14×10^{-9})	-1.59×10^{-8} *** (4.33×10^{-9})	1.90×10^{-9} (2.04×10^{-9})	1.01×10^{-8} (1.18×10^{-8})	-1.50×10^{-8} *** (3.96×10^{-9})
LEV	0.0004629 *** (0.0000712)	0.0027879 *** (0.0003561)	0.0057354 *** (0.0005301)	0.0005246 (0.0003175)	0.0030618 ** (0.0014202)	0.0057383 *** (0.0020397)	0.0004468 *** (0.0000738)	0.0027764 *** (0.0003767)	0.0058464 *** (0.0006052)	0.000375 ** (0.0001699)	0.0022908 ** (0.0009509)	0.0062646 *** (0.0004938)
SZ	0.0001039 *** (7.55×10^{-6})	0.0005545 *** (0.0000787)	0.001058 *** (0.0000586)	0.0002252 (0.0001478)	0.0014542 ** (0.0006258)	0.0030012 *** (0.0008581)	0.0001207 *** (9.37×10^{-6})	0.0005844 *** (0.0000862)	0.0010013 *** (0.000219)	−0.0000768 * (0.0000409)	−0.0004229 (0.0002954)	0.0002316 (0.000193)
ROA	−0.0005044 *** (0.0000935)	−0.0031202 *** (0.0004597)	−0.005054 *** (0.0004974)	−0.0000804 (0.0011853)	−0.0009847 (0.004922)	−0.001876 (0.0063292)	−0.0005243 *** (0.0000944)	−0.0032617 *** (0.0004481)	−0.0035032 *** (0.0007589)	−0.0027113 *** (0.0010163)	−0.0165086 *** (0.00603)	−0.003885 *** (0.0007235)
BM	1.51×10^{-8} (2.48×10^{-8})	3.31×10^{-7} * (1.58×10^{-7})	1.13×10^{-6} *** (1.46×10^{-7})	-3.82×10^{-7} (5.33×10^{-7})	-2.29×10^{-6} (2.35×10^{-6})	-4.57×10^{-6} (3.56×10^{-6})	3.85×10^{-8} * (2.27×10^{-8})	4.45×10^{-7} *** (1.33×10^{-7})	2.37×10^{-6} (2.67×10^{-6})	4.48×10^{-7} *** (1.42×10^{-7})	2.75×10^{-6} *** (8.26×10^{-7})	3.33×10^{-6} (2.16×10^{-6})
Cons	−0.0008388 *** (0.000115)	−0.0046748 *** (0.000576)	−0.0113189 *** (0.0007283)	−0.0019165 (0.0017337)	−0.012897 * (0.0072475)	−0.0276811 *** (0.0093666)	−0.0010337 *** (0.0001065)	−0.0052862 *** (0.0005935)	−0.0099221 *** (0.0013581)	0.0003866 (0.0004381)	0.0023168 (0.0024475)	−0.0100079 *** (0.0011373)
Obs.	795	795	795	795	795	795	795	795	795	795	795	795
AR (2)	0.211 (−1.25)	0.163 (−1.39)	0.130 (−1.51)	0.281 (−1.08)	0.232 (−1.20)	0.223 (−1.22)	0.240 (−1.18)	0.186 (−1.32)	0.111 (−1.59)	0.526 (−0.63)	0.550 (−0.60)	0.122 (−1.54)
Hansen	0.499 (20.36)	0.381 (22.32)	0.190 (36.56)	0.849 (7.13)	0.734 (8.63)	0.548 (10.77)	0.195 (26.31)	0.190 (26.46)	0.405 (27.08)	0.931 (5.69)	0.870 (6.81)	0.296 (37.90)
Model efficacy	√	√	√	√			√	√	√	√	√	√

Notes: *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively. √ indicates models are valid.

6. Discussion and Conclusions

6.1. Evaluating the Impact of ESG and Its Pillars

The estimation results confirm that the overall ESG score exerts a significant adverse effect on firm-level probability of default (PD), thereby supporting Hypothesis 1, which posits that strong ESG performance mitigates firm default risk. This finding aligns with recent studies by H. Li and Hu (2025), H. Li et al. (2022), Maquieira et al. (2024), and Liu and Zhang (2024), all of which emphasize ESG's role in enhancing corporate financial resilience.

When decomposing the ESG score into its three constituent pillars, results reveal a heterogeneous impact. Both the Environmental (E) and Social (S) dimensions exhibit a significant negative association with default risk across all time horizons, short-term (1-month), medium-term (6-month), and long-term (12-month), suggesting that these aspects contribute to firm stability and reduce credit risk. In contrast, the Governance (G) pillar shows a positive relationship with default risk in all term structures. These findings support Hypothesis 2, which anticipated differentiated effects from individual ESG components on credit risk.

Moreover, the impact of ESG on PD intensifies over longer time horizons. For the overall ESG score, the estimated risk-reducing effect increases from 0.000798% in the short term to 0.004% in the medium term and 0.0097% in the long term. A similar trend is observed for the E pillar, where the coefficient increases from 0.000852% (1 month) to 0.00407% (6 months) and 0.00919% (12 months). The S pillar also demonstrates increasing influence, with PD reductions rising from 0.000856% to 0.00433% and 0.00687% over the same respective horizons. Conversely, the G pillar, despite its positive relationship with PD, shows an escalating risk effect: 0.0012% in the short term, 0.004% in the medium term, and 0.00831% in the long term.

These findings highlight the informational content and credit relevance of ESG metrics in the Australian market. Notably, while overall ESG scores and the E and S pillars contribute meaningfully to credit risk mitigation, the G pillar appears to increase default risk, potentially reflecting complexities or inefficiencies in governance mechanisms among Australian-listed firms. This nuanced pattern is consistent with prior literature, including Nguyen et al. (2020), Jiraporn et al. (2014), and Lin et al. (2015), and underscores the importance of pillar-level analysis in ESG-financial risk research.

The consistently higher G scores observed in Table 1 suggest that Australian firms tend to emphasize governance-related disclosures and compliance more heavily than environmental or social initiatives. While this emphasis aligns with regulatory expectations and investor pressure, it may also indicate an over-reliance on formal governance mechanisms that do not directly mitigate operational or sustainability-related risks. This imbalance could explain why the G pillar, despite its traditionally assumed protective role, exhibits a positive relationship with default risk in our findings. In addition, firms may engage in greenwashing in governance when they could optimize for scoring criteria without actually improving governance. Yu et al. (2020) indicate that good ESG performance firms that perform poorly in ESG activities can be categorized as "greenwashers".

6.2. Trade Credit Financing Mediating in the ESG–Default Risk Relationship

Table 5 presents a negative relationship between TCF and ESG performance, both in the overall score and across its individual pillars. This indicates that firms with lower ESG scores tend to rely more heavily on trade credit financing, while those with stronger ESG profiles maintain better liquidity and use less TCF.

Further insights are provided in Table 6, which examines TCF as a mediating variable in the ESG–default risk nexus. When TCF is incorporated into the mediation model (Equation (3)), it displays a positive and significant coefficient, suggesting that higher reliance on TCF is associated with an increased likelihood of firm default. Although the ESG overall score, along with the E and S pillars, continues to show a negative relationship with default risk, the strength of these relationships diminishes across all term structures (1-month, 6-month, and 12-month) compared to those in Table 4, indicating a partial mediation effect. In essence, TCF dampens the risk-reduction benefit of ESG, confirming its role as a partial mediator. Interestingly, when TCF mediates the link between the G pillar and default risk, it intensifies the positive association, suggesting that greater use of TCF exacerbates the risk impact tied to governance-related ESG activities. These findings offer empirical evidence for Hypothesis 3, emphasizing the partial mediating role in the ESG-default relationship.

This relationship is supported by capital structure theory, which holds that firms with a debt ratio (total liabilities to total assets) of less than one is generally in a healthy financial position. However, firms with high TCF, measured by the sum of accounts receivable, accounts payable, and notes payable relative to total assets, may still encounter credit risk. A high ratio of accounts receivable indicates significant capital tied up with customers, reflecting a drain on liquidity. Reducing this burden can improve cash flow and reduce financial distress.

From the perspective of working capital management, Baños-Caballero et al. (2012) argue that excessive investment in working capital, such as extended trade credit or large inventories, can negatively impact firm performance. Similarly, Deloof (2003) notes that shortened trade credit cycles may compromise firms' ability to assess product quality, potentially harming profitability. Soenen (1993) further suggests that excessive working capital investments may even lead to bankruptcy.

In contrast, firms with strong ESG performance typically exhibit superior financial and operational management. As highlighted by Buallay (2019), sustainability reporting, a key ESG component, is linked to enhanced financial performance and operational efficiency. These firms often enforce stricter credit policies, conduct more rigorous risk assessments, and manage debt collection processes more effectively, resulting in lower accounts receivable and improved liquidity.

Furthermore, high-ESG firms often benefit from greater access to low-cost external financing (e.g., bank loans or bonds), allowing them to pay suppliers early and take advantage of discounts, which leads to reduced accounts payable. This operational strength is supported by trade-off theory, which suggests that high-ESG firms balance short-term profit motives with long-term sustainability objectives. Such firms are more likely to prioritize stable operations and liquidity over immediate gains.

According to Jose et al. (1996), liquidity management, particularly operating cash flow, is a cornerstone of a firm's long-term viability. Strong ESG performers are more likely to maintain positive cash flows, which in turn helps them meet financial obligations and avoid default. On the other hand, as explained by Wang (2002), poor liquidity impairs a firm's ability to seize investment opportunities and fulfil debt obligations, increasing the risk of financial distress or even insolvency.

6.3. Lagged ESG Effect and Firm's Default Risk

Table 7 presents the results examining the effect of one-period lagged ESG overall scores and individual pillar scores (E, S, and G) on firm default risk across different time horizons. The findings reveal a significant and persistent influence of lagged ESG variables on default probabilities in the short (1-month), medium (6-month), and long-term (12-month) structures. Notably, the coefficients associated with the lagged ESG overall score and each of the ESG pillars are larger in magnitude than those observed in the contemporaneous models, as presented in earlier tables. This suggests that the impact of ESG performance on a firm's default risk is not only sustained but also intensifies over time.

The results imply that ESG performance may require time to be fully priced into a firm's credit risk profile, reflecting a delayed recognition or gradual transmission of ESG signals in financial markets. This temporal persistence reinforces the relevance of ESG as a forward-looking indicator of creditworthiness and highlights the importance of incorporating lagged ESG variables in modelling firm risk dynamics. Importantly, these patterns remain consistent across all examined term structures, underscoring the robustness of the delayed ESG-default risk relationship.

6.4. Two Samples: Industrial and Non-Industrials

Tables 8 and 9 show that the overall ESG score and its individual pillars significantly influence a firm's default risk in both industrial and non-industrial samples. The results are consistent across both groups and closely aligned with the full-sample findings, confirming that the negative association between ESG (particularly environmental and social pillars) and default risk is generalizable across Australian firms. This evidence strengthens the argument that ESG's risk-reducing effect extends beyond industry-specific dynamics and reflects a broader, systemic influence within the corporate landscape.

6.5. Indirect Approach and Black-Box Concern

This study adopts an indirect approach by analyzing the association between ESG performance and default probabilities produced by the CRI model, which operates as an external, proprietary credit risk framework. While the underlying CRI methodology is not specific to Australian firms, its globally calibrated nature enhances comparability across markets. We acknowledge that there is a black-box concern, i.e., since the internal parameter weights and transformations within the CRI model are not fully disclosed, the precise functional link between input variables and PD outcomes cannot be directly observed. However, our research design mitigates this limitation in two ways. First, we explicitly confirm that ESG measures are not included as explanatory variables in the CRI model, ensuring that the PDs are generated independently of the ESG data under analysis. Second, by employing the Generalized Method of Moments (GMM) estimator, we address potential endogeneity arising from systematic dependence between variables used in the CRI model and our ESG-related measures. As a result, the observed relationships between ESG performance and CRI-generated PDs can be interpreted as reflecting an ex-post association between sustainability characteristics and externally modelled credit risk, providing valuable insights for investors and policymakers despite the proprietary nature of the PD estimation process.

6.6. Research Significance

6.6.1. ESG and the Firm's Governance

While ESG overall and E, S scores have a negative impact on a firm's default risk, the G pillar score has the opposite direction. However, the G pillar increases this risk for Australian-listed firms. The explanation could be that effective management isn't always reflected in the G score. Businesses may, for instance, achieve a high score of G on certain measures, such as board independence, but yet be vulnerable to inferior execution and strategy, as well as excessive compliance costs that could put them at financial risk. Additionally, when a company optimizes for scoring criteria without genuinely enhancing governance, it may participate in greenwashing to meet stakeholder expectations.

The Financial Services Royal Commission (2017–2019) revealed that stringent governance requirements, such as those imposed post-Hayne Report, increased administrative burdens without necessarily improving risk oversight. Firms with high G-scores may incur elevated compliance costs (e.g., reporting, audits), diverting resources from core operations and exacerbating financial strain.

Australia's resource-dominated economy (mining, energy) faces governance complexities where environmental and social risks (e.g., community conflicts, climate litigation) are misaligned with traditional governance metrics. A high G-score in these sectors may mask unresolved operational risks, as noted by Lin et al. (2015) in their study of governance and CSR trade-offs.

While governance improvements may yield long-term stability, short-term disruptions (e.g., leadership transitions, policy overhauls) could temporarily elevate default risk. This is consistent with our lagged models (Table 7), where the G-pillar's positive effect persists but diminishes over time. These findings caution against overreliance on aggregate governance scores and highlight the need for granular, context-specific metrics, particularly in markets like Australia, where governance reforms are recent and sectoral risks are pronounced.

6.6.2. Financial Managers and Investors

Investors can utilize the score of ESG overall and pillar-level as risk indicators by emphasizing environmental and social dimensions to improve portfolio performance. The study conveys the message that investors should evaluate ESG implications at a disaggregated level for comprehensive assessment and to avoid mispriced risk. Businesses should understand that not all areas benefit equally from ESG investing. Environmental and social initiatives may offer risk mitigation influence, while governance should be examined in different dimensions. ESG strategies, particularly in governance, should be enhanced to increase intrinsic value, thereby creating an accurate perception among external stakeholders to achieve sustainable development.

6.6.3. Trade Credit Financing: Trade-Off to Sustainable Development

The study confirms that trade credit financing functions as a mediating factor, significantly weakening the risk-reducing potential of ESG. Using more trade credit financing may cause firms to have liquidity issues, leading to a higher probability of default risks in different sector groups. From an ESG preference perspective, firms maintain a working capital balance for the long term, reduce the funding obtained from their business partners to improve their reputation, and reduce their debt burden. In addition, decreasing the amount of trade credit given to customers can help assure liquidity and long-term equilibrium.

Although ESG performance is typically regarded as a long-term investment, its effects can manifest in the short run through channels that directly influence firms' ability to access and manage trade credit. For instance, firms with stronger ESG performance, particularly in environmental and social dimensions, often enjoy better stakeholder trust, stronger supplier relationships, and improved reputation. These attributes can reduce the likelihood of suppliers withdrawing or tightening trade credit, even in the short term. Conversely, weaker ESG performance may heighten perceptions of operational or reputational risk, prompting suppliers to restrict credit availability, which can increase default risk on TCF obligations even within a one-month horizon. ESG performance also acts as a signaling mechanism in capital and credit markets. Firms with strong ESG credentials may be perceived as more transparent and reliable, thereby receiving more favorable short-term credit terms. This signaling channel provides an immediate link between ESG values and short-term default probabilities on trade credit. We acknowledge that ESG is inherently long-term, but by examining its relationship with short-term default probabilities, we are testing whether these structural ESG characteristics have spillover effects into short-horizon credit risk measures. The evidence suggests that ESG-related strengths or weaknesses are indeed priced into even short-term credit risk expectations.

6.6.4. Different Term Structure of Probability of Default

The ESG–default risk relationship is examined across different time horizons, including short-term (1-month), medium-term (6-month), and long-term (12-month) default probabilities. The findings reveal that the risk-mitigating effect of ESG performance strengthens over time, suggesting that firms with strong ESG practices are consistently less likely to default. This may imply that such firms enjoy lower financing costs and enhanced competitiveness relative to their lower ESG-rated counterparts within the same industry.

6.7. Policy and Practical Implications

Our findings carry several implications for corporate managers, investors, and regulators. For corporate managers, the results suggest that ESG adoption, particularly in the environmental and social dimensions, can play a stabilizing role by lowering long-term default risk. Firms should view ESG not merely as a compliance or reputational exercise but as a strategic investment in risk resilience. At the same time, the positive association between the governance pillar and default risk indicates that governance signals in ESG ratings may not always translate into lower credit risk. This could reflect instances of symbolic governance or "box-ticking" practices that inflate governance scores without meaningfully improving financial resilience. Managers should therefore focus on the substance of governance practices (e.g., risk oversight, board independence, transparent reporting) rather than symbolic compliance.

For investors, the results highlight the need to interpret governance-heavy ESG scores with caution. A higher governance rating does not necessarily imply lower firm risk; rather, investors may need to consider whether governance improvements are substantive or cosmetic. This calls for more granular due diligence into firm-level governance practices beyond rating agency scores.

For regulators, the findings underscore the importance of enhancing ESG disclosure frameworks to improve the reliability of governance indicators. Clearer guidelines on what constitutes material governance practices could help reduce the risk of greenwashing and provide investors with more consistent signals. Regulators might also consider targeted oversight of industries where governance risks are more likely to translate into default probabilities, such as highly leveraged or carbon-intensive sectors.

6.8. Future Research: Ownership Structures and ESG–Risk Dynamics

Although ownership structures were not directly observable in our dataset, our literature review suggests that they may play a critical role in shaping the relationship between ESG practices and default risk. Family-owned firms are often characterized by longer investment horizons, reputational concerns, and stronger emphasis on intergenerational sustainability, which may encourage alignment with ESG principles as a means of preserving firm value. In contrast, institutional investors tend to advocate for more formalized governance practices, stricter disclosure, and compliance mechanisms, potentially intensifying the governance–performance link. These divergent ownership incentives could act as moderators in the ESG–risk nexus, particularly in explaining variations in how governance practices influence default probability across firms. While our findings provide robust evidence of the direct and mediating roles of ESG and trade credit financing, we acknowledge that incorporating ownership heterogeneity may reveal additional nuances. Future research could extend this line of inquiry by examining how family versus institutional ownership moderates ESG's influence on financing choices and credit risk outcomes in the Australian context.

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